Journal of Cleaner Production 202 (2018) 883–891

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

CO_2 emissions and poverty alleviation in China: An empirical study based on municipal panel data

Gui Jin [a, b], Rao Fu [a], Zhihui Li [b, c, d, *], Feng Wu [b, c, d], Fan Zhang [b, c]

[a] Faculty of Resources and Environmental Science, Hubei University, Wuhan 430062, China
[b] Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China
[c] Center for Chinese Agricultural Policy, Chinese Academy of Sciences, Beijing 100101, China
[d] University of Chinese Academy of Sciences, Beijing, 100049, China

ARTICLE INFO

Article history:
Received 30 March 2018
Received in revised form
6 August 2018
Accepted 20 August 2018
Available online 22 August 2018

Keywords:
CO_2 emissions
Climate change
Social poverty
Influencing mechanism
Simultaneous equations
China

ABSTRACT

Industrial transition and climate change regulation to reduce CO_2 emissions will affect employment and further influence social poverty. In this study, we measured CO_2 emissions and the poverty-alleviation index based on socio-economic and energy consumption statistic data from 286 municipal cities in China for 2007–2014; analyzed relationships between CO_2 emissions, employment rate, and poverty-alleviation index using simultaneous equations; and interpreted the mechanism by which CO_2 emissions influence social poverty at the municipal level. The results indicate that average CO_2 emissions from China increased by 32.9%, with a rapid initial rise and then steady growth from 2007 to 2014, while the average poverty-alleviation index increased by 25.19% during the same period. CO_2 emissions had a significant positive relationship with employment rate in all industries. In addition, employment rate was negatively correlated with poverty-alleviation in primary industry and positively correlated with poverty-alleviation in non-agricultural industry. Studying the mechanisms for CO_2 emission impacts on poverty-alleviation can provide important references for adapting to global climate change, promoting sustainable development, and safeguarding the legitimate development rights of all countries, especially developing countries.

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1. Introduction

Poverty alleviation and CO_2 emissions reduction are two of China's ongoing strategic missions. Poverty alleviation assists poor households and areas by improving skills and income through physical infrastructure construction, social development, and industrial development, which will help China achieve its goal of comprehensive poverty elimination in 2020 (Liu et al., 2016). To reduce CO_2 emissions in the context of Paris Agreement, China has submitted its Intended Nationally Determined Contributions towards achieving the goals by 2030 as follows: China's CO_2 emissions per unit GDP will be 60% lower than 2005, the proportion of non-fossil fuels in total energy consumption will increase to around 20%, CO_2 emissions will reach its peak in 2030, and carbon storage in forest reserves will increase 4.5 billion cubic meters (Deng et al., 2009; Deng et al., 2012; Schreurs, 2016). Poverty alleviation and CO_2 emissions reduction are closely related (Bai et al., 2017; Chen et al., 2017; Glomsrød et al., 2016). Working Group III in the IPCC Fifth Assessment Report (IPCC AR5) indicated that resolving climate change issues within the framework of sustainable development needs to contain social-economic-environmental integrated goals to ultimately maximize the synergies of the three. In the process of climate change mitigation, the public often focuses on the direct and indirect costs of emission reduction, neglecting the synergies that result from changes in employment and income and changes in energy and resource consumption patterns. Addressing climate issues requires actively implementing emission reductions, which will inevitably limit the development of energy and its subordinate sectors, affect the continued expansion of the national economy, and hinder poverty alleviation (Alexander, 2016; Zhang et al., 2017a,b,c; Wiedenhofer et al., 2016). However, the mechanisms influencing the combination of CO_2 emissions reduction, economic development, and poverty alleviation remains unclear, which is a pivotal scientific issue for China while improving poverty-

* Corresponding author. Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China.
E-mail addresses: jingui@hubu.edu.cn (G. Jin), frr_simlab@163.com (R. Fu), lizhihui@igsnrr.ac.cn (Z. Li), wufeng@igsnrr.ac.cn (F. Wu), zhangf.ccap@igsnrr.ac.cn (F. Zhang).

https://doi.org/10.1016/j.jclepro.2018.08.221
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alleviation performance and achieving CO_2 emissions reduction goals (Deng et al., 2013; HoeghGuldberg and Bruno, 2010). The IPCC AR5 suggested that social transition and climate change due to CO_2 emissions or CO_2 emissions reduction will further exert effects on nature and human well-being, especially on livelihood and poverty (Riahi, 2014; Trenberth et al., 2015). For example, CO_2 emissions reduction measures will lead to industrial transition in the long term, affect resident employment and livelihood, and increase the uncertainty and unknown risks of poverty-alleviation project implementations in the short term (Morfeldt et al., 2015; Zhang et al., 2017a,b,c).

The Chinese government has enacted mid-and-long term anti-poverty development planning and a series of anti-poverty policies targeted at the rural poor population (Liu and Li, 2017). Those actions have resulted in a dramatic decrease in poverty-stricken population (Bank, 2009; Heilig et al., 2006; Huang et al., 2006). However, poverty alleviation actions rarely account for the effects of CO_2 emissions and emissions reduction because the relevant theories have been considered unscientific or unreasonable and usually oppugned by academics (Chen et al., 2016; Park and Wang, 2010; Li et al., 2016a,b). In recent years, pioneering scholars have made initial attempts to explore the potential relationship and feedbacks between reducing CO_2 emissions and anti-poverty measures. Davies et al. (2014) and Hyder (2008) achieved the goal of curbing high CO_2 emissions while also developing employment opportunities by collecting carbon taxes. Chang (2015) analyzed the relationship between CO_2 emissions and resident income in a poverty-stricken area through studying industrial transitions. The relationships between economic development, poverty, and energy consumption have been analyzed in different studies (Sharma, 2010; Wang et al., 2016a,b; Zhang and Wang, 2014; Zhang et al., 2017a,b,c), which are the first steps towards CO_2 emissions reduction and poverty alleviation. However, these studies were mostly single-objective analyses focused on achieving both poverty alleviation and CO_2 emissions reduction, and few studies have comprehensively analyzed mechanisms of their mutual influence (Jin et al., 2017; Hallegatte et al., 2016; Hubacek et al., 2017). Further practical and theoretical work is needed to obtain systematic and scientific key results that reveal relationships between CO_2 emissions and social poverty.

Thus, in this study, our goal was to measure CO_2 emissions and the poverty-alleviation index based on socio-economic and energy consumption statistic data from 286 municipal cities in China for 2007–2014 and further analyze the relationships between CO_2 emissions, employment rate, and poverty-alleviation index at the municipal level. This research will provide a scientific and political basis for implementing China's ongoing poverty alleviation and CO_2 emission reduction strategies.

2. Data and methods

2.1. Study area

IPCC AR5 highlighted the continued rise in global greenhouse gas emissions from 2010 to 2014, where China's CO_2 emissions ranked first in the world since 2007 (IEA, 2007). As a rapidly developing country, China has continuously strengthened its efforts to reduce CO_2 emissions (Zhang and Hao, 2015). However, the energy consumption and CO_2 emission structure at the provincial level in China are different. CO_2 emissions from the electric power sector have always been China's primary emissions source, followed by emissions from the transportation, heating, and gas supply sectors (Wiedenhofer et al., 2016). In 2015, China announced that CO_2 emissions are expected to peak around 2030, with CO_2 emissions per unit GDP decreasing by 60–65% compared with that in 2005 (Miao, 2013; Tollefson, 2016). To achieve China's emissions-reduction goals will sacrifice more socio-economic development chances (Crane et al., 2011), and even affect employment and well-being (Tiezzi, 2005). This could increase the risk to China's ongoing anti-poverty projects and result in re-poverty or new social poverty (Sharma and Chowdhary, 2015). The 5th Plenary Session of the 18th Central Committee of the Chinese Communist Party proposed achieving full poverty-elimination goals nationally by 2020. In this context, clarifying the mechanisms by which CO_2 emissions will impact social poverty and ensure China's smooth realization of poverty-alleviation and CO_2 emissions reduction goals. Considering data availability, our study area covers 286 of the 333 municipal-level cities in China (Fig. 1), among which municipal-level cities with missing data are primarily located in the west.

2.2. Data processing

Four types of energy consumption data are used to measure municipal-city level CO_2 emissions, including electricity, gas, transportation vehicle, and central-heating consumption data (Zhang and Xie, 2015). These data are derived from the Chinese Regional Economic Statistical Yearbook (2008–2015), Chinese Cities Statistical Yearbook (2008–2015) and Chinese Cities Construction Statistical Yearbook (2008–2015) (http://www.stats.gov.cn/tjsj/), prefecture and city statistical yearbooks, and statistical bulletin for national economy and social development.

Socio-economic data are applied to calculate the poverty-alleviation index and analyze the influencing mechanism. Data to calculate the poverty-alleviation index include disposable urban resident income, net income per rural capita, GDP per capita, gross investment in fixed assets, total social retail sales, number of enrolled students per 10,000 people, public library books per 100 people, beds in medical and health institutions per 10,000 people, social security coverage ratio, and internet prevalence ratio. Data used to analyze the influencing mechanism using a series of simultaneous equations include employment rate, income, investment, GDP, education expenditure, and urbanization rate. These data are from the Chinese Cities' Construction Statistical Yearbook (2008–2015) (http://www.stats.gov.cn/tjsj/), local statistical bulletins, and statistical bureau websites.

Meteorological data are collected from the China Meteorological Bureau (http://data.cma.cn), including daily observation data, i.e., average daily temperature and precipitation. Accumulated temperate values above 0 °C are calculated based on daily average temperature data. Raster data for average annual temperature and precipitation in 1 km × 1 km grid size are generated using the Kriging interpolation method. Then, average temperature and precipitation values at the municipal level are calculated. Additional data details are provided in Table 1.

2.3. Methods

2.3.1. Calculating CO_2 emissions

CO_2 emissions were calculated according to IPCC Greenhouse Gas Emission Inventory Guide (Garg and Pulles, 2006; Nep and Iea, 2006). Total CO_2 emissions at the municipal level are generated based on four factors: electricity, gas, transportation and central heating.

Electricity CO_2 emissions (C_1, ton) are calculated as follows:

$$C_1 = E_1 \times EF_{1i} \quad (1)$$

where, E_1 refers to electricity consumption for the whole city (10^4 kwh) and EF_{li} represents the CO_2 emissions factor for the electric power grid ($tCO_2/10^4$kwh).

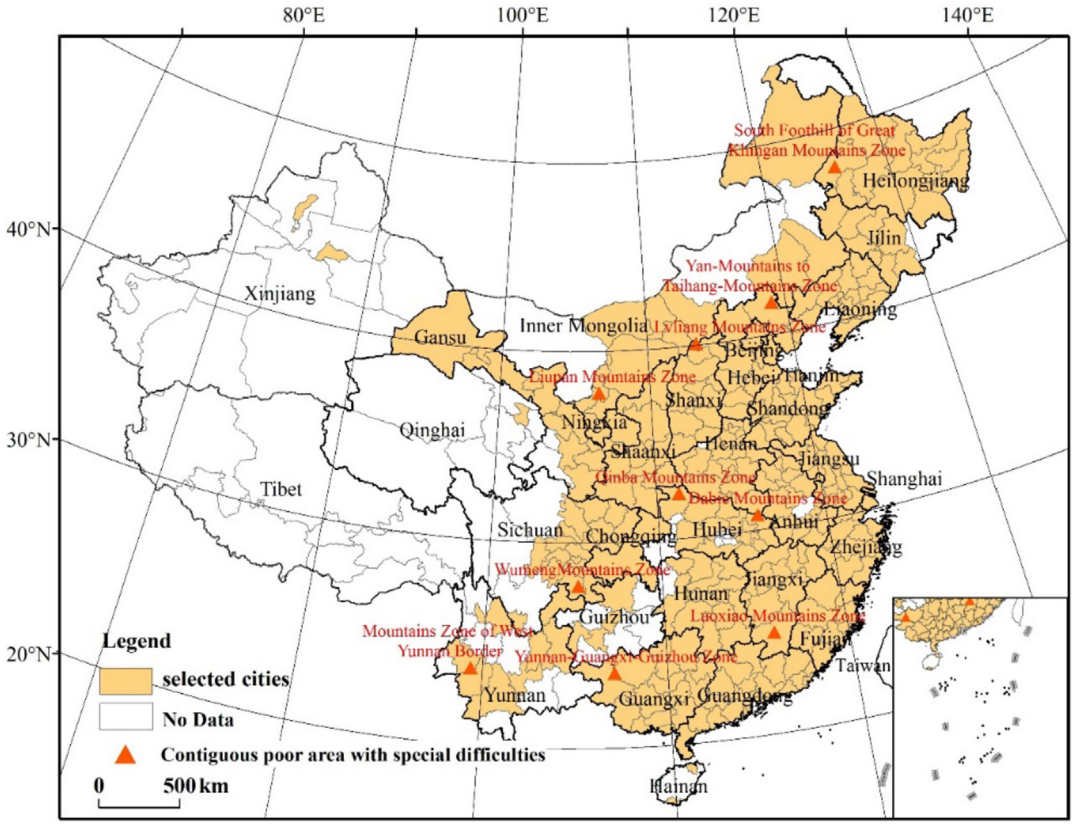

Fig. 1. Locations and distribution of selected municipal-level cities in China.

Table 1
Variable and data descriptions for selected municipal-level cities in China.

Variable (unit)	Min	Max	Std. Dev	Mean
Disposal income of urban residents (yuan)	8788	39625.09	6414.65	18742.16
Net income per rural capita (yuan)	2374	21239.8	3679.88	7696.62
GDP per capita (yuan)	6012.08	215613.1	36538.6	38449.68
Total social retail sales (100 million yuan)	295683	4.48e+07	7577498	5725409
Investment in fixed assets (100 million yuan)	702888	5.97e+07	1.08e+07	9898038
Enrolled students per 10000 people (person)	975.92	3519.91	474.05	1766.32
Public library books (100 person/copy)	4.54	453.56	63.97	49.51
Beds of health institutions (10000 person/bed)	12.78	86.45	14.85	36.82
Internet penetration (%)	1.105	82.22	13.03	12.37
Social security coverage ratio (%)	3.02	146.93	26.01	28.43
Primary industry employment (%)	0.0077	27.78	3.957	1.74
Non-agricultural industries employment (%)	23.11	77.75	11.93	50.99
Foreign capital actually utilized (%)	0.0122	17.19	3.40	2.925623
Annual growth rate of per capita GDP (%)	1.5	22	3.488	12.42792
Education expenditure (100 million yuan)	40251	3023241	413311.3	388049.8
Urbanization rate (%)	2.882	98.34	8.96	11.23
Annual average temperature (°C)	1.91	23.6	5.17	14.84
Annual precipitation (mm)	92.28	2728.4	555.95	967.51

Gas CO_2 emissions (C_2, ton) are calculated as follows:

$$C_2 = F_1 \times NVI_1 \times EF_2 \times F_2 \times NVI_2 \times EF_3 \times M_1 + F_3 \times NVI_3 \times EF_4 \times M_2 \quad (2)$$

where, F_1, F_2, and F_3 respectively represent the citywide consumption of liquefied (ton), coal, and natural gas (10^4 m^3); NVI_1, NVI_2 and NVI_3 refer to the calorific values of liquefied, coal, and natural gas (i.e., 50.179 MJ/kg, 38.931 MJ/m^3, and 38.7 MJ/kg); EF_2, EF_3, and EF_4 represent CO_2 emission factors for liquefied, coal, and natural gas with respective values of 0.06307 kgCO_2/MJ, 0.0561 kgCO_2/MJ and 0.0444 kgCO_2/MJ; M_1 and M_2 are coal gas and liquefied density with respective values of 0.45 kg/m^3 and 0.717 kg/m^3.

Transportations CO_2 emissions (C_3, ton) are calculated as follows:

$$C_3 = Q_1 L_1 \lambda_1 k_1 + Q_{21} L_{21} \lambda_{21} k_{21} + Q_{22} L_{22} \lambda_{42} k_{22} + Q_3 L_3 \lambda_3 k_{21} \quad (3)$$

where, Q_1, Q_{21}, Q_{22}, and Q_3 represent the number of buses, gasoline-

engine taxis, natural gas-engine taxis, and private cars, respectively; L_1, L_{21}, L_{22}, and L_3 are their respective mileages (km/year); and λ_1, λ_{21}, λ_{22}, and λ_3 are their relevant fuel (gas) consumption coefficients (L/km). Relevant research results based on the status quo of China's energy consumption (Tang et al., 2016) indicate that the bus speed is 16 km/h, daily travel time is 12 h per day, and gasoline consumption is 40 L/100 km. Natural gas station and gas sales volume in each city are used to identify gasoline-engine or natural gas-engine taxis; taxis travel distance is 182,500 km/year, gasoline consumption and taxi gasoline consumption are 9.945 L/100 km and 9.8 L/100 km respectively; for private cars, travel distance is 15,000 km/year and gasoline consumption is 8.8 L/100 km k_1, k_{21}, and k_{22} represent the CO_2 emissions coefficients for diesel, gasoline, and natural gas with respective values of 2.7 kg/L, 2.314 kg/L, and 2.1869 kg/m^3).

Central heating CO_2 emissions (C_4, ton) are calculated as follows:

$$C_4 = S \times N \times EF_5 \tag{4}$$

where, S denotes the central heating size (m^2), N refers to coal-consumption for central heating per unit area (kg/m^2), and EF_5 is the standard CO_2 emission factor for coal (2.46 kgCO_2/kg).

The total CO_2 emissions from energy consumption is the sum of C_1, C_2, C_3, and C_4.

2.3.2. Calculating the poverty-alleviation index

The multidimensional poverty model poorly reflects poverty-alleviation progress as it identifies regional multidimensional poverty only at a given point in time and ignores the dynamic process of regional poverty. Therefore, our goal is to analyze the spatiotemporal patterns in regional poverty using the dynamic degree of poverty alleviation (Alkire and Santos, 2014; Jin et al., 2018; Qi and Wu, 2015; Yu, 2013). In this research, we logically measured social poverty according to the poverty-alleviation degree and its evolution. The poverty-alleviation index system was constructed from both material and civilization dimensions (Woods, 2003). Material poverty alleviation indicators include net income per rural capita, disposable income of urban residents, per capita GDP, gross investment in fixed assets, and social consumable total retail sales. Civilization poverty indicators include the number of enrolled students, public library books per capita, the number of beds in medical and health institutions, the number of people with social security, and internet availability (Molina and Morales, 2010). Then, indicators are processed as non-dimensional, standardized, and same-directional for consistency with the definition of the poverty-alleviation index and according to influential disparities. In this study, a comprehensive index model is proposed to evaluate the poverty-alleviation index at the municipal level as follows:

$$pov^t = \sum_{i=1}^{n} w_i y_i^t \tag{5}$$

where, pov^t refers to the poverty-alleviation index of the t_{th} period; y_i^t is the poverty indicators based on standardization in the t_{th} period, which include material poverty alleviation data and civilization poverty alleviation data; w_i represents the index weight; and i represents the ith indicator. The hierarchical analytical method and Delphi method are adopted to determine weights. Normalized processing for indicators is implemented according to the degrees of influential disparities.

2.3.3. Model with simultaneous equations

The final objective of this study is to interpret the relationships between CO_2 emissions and poverty alleviation, and to reveal the mechanism of their mutual influence. We employ a model with simultaneous equations to account for the structural relationships for the multiple results and analyze the complex relationship between CO_2 emissions and poverty alleviation. We adopt the iteration 3 stages' least square method (IT3SLS) to overcome the limitations of the iteration 2 stages' least square method and ensure the consistency of model estimation results by minimizing the generalized residual error (Ojha, 2008; Jin et al., 2015; Hallegatte et al., 2016). The process and mechanism of mutual influence are combined to construct the simultaneous equations model (Equation (6)). The relationships between the four factors are revealed, i.e., the mechanism influencing poverty-alleviation index and employment rates; employment rate in primary industry, CO_2 emissions, and climate elements; employment rate in non-agricultural industries and CO_2 emissions; and CO_2 emissions and employment rates in both primary and non-agricultural industries.

$$\begin{cases} \ln pov_{it} = \alpha_0 + \alpha_1 \ln em_f_{it} + \alpha_2 \ln em_st_{it} + \alpha_3 \ln inc_d_{it} + \alpha_4 \ln for_u_{it} \\ \ln em_f_{it} = \beta_0 + \beta_1 \ln pov_{it} + \beta_2 \ln co_{2_{it}} + \beta_3 \ln tem_{it} + \beta_4 \ln rain_{it} \\ \ln em_st_{it} = \gamma_0 + \gamma_1 \ln pov_{it} + \gamma_2 \ln co_{2_{it}} + \gamma_3 \ln gdp_g_{it} + \gamma_4 \ln edu_{it} \\ \ln CO_{2_t} = \phi_0 + \phi_1 \ln em_f_{it} + \phi_2 \ln em_st_{it} + \phi_3 \ln for_u_{it} + \phi_4 \ln urban_{it} \end{cases} \tag{6}$$

In these simultaneous equations, t represents a particular year; i is the municipal unit; α_0, β_0, γ_0 and φ_0 are error terms; pov refers to the poverty alleviation index; em_f is the employment rate in primary industry; em_st is the employment rate in non-agricultural industries; gdp_g is annual growth rate per capita GDP; $urban$ is the urbanization rate; CO_2 is CO_2 emissions; tem is the annual average temperature; $rain$ represents annual precipitation; inc_d is net income per rural capita; for_u is amount of foreign capital actually utilized; and edu is education expenditure. Moreover, the employment rate in the primary and non-agricultural industries respectively refer to the ratio of employed population in the primary industry and non-agricultural industries to the total working population and the non-agricultural ratio is the ratio of non-agricultural output to total gross domestic output.

3. Results

3.1. CO_2 emissions

CO_2 emissions from the 286 municipal cities in China are used to determine the spatiotemporal patterns of CO_2 emissions at the municipal level (Fig. 2). The results show that the four types of CO_2 emissions increased annually (2007–2014). The spatial distribution pattern of electricity, gas, and transportation CO_2 emissions showed highs in the east and lows in the west, while that for central heating CO_2 emissions showed highs in the north and lows in the south. The average total CO_2 emissions from the 286 municipal cities increased by 32.9% from 2007 to 2014 with an initial rapid rise and then steady growth. Before 2011, the rate increased

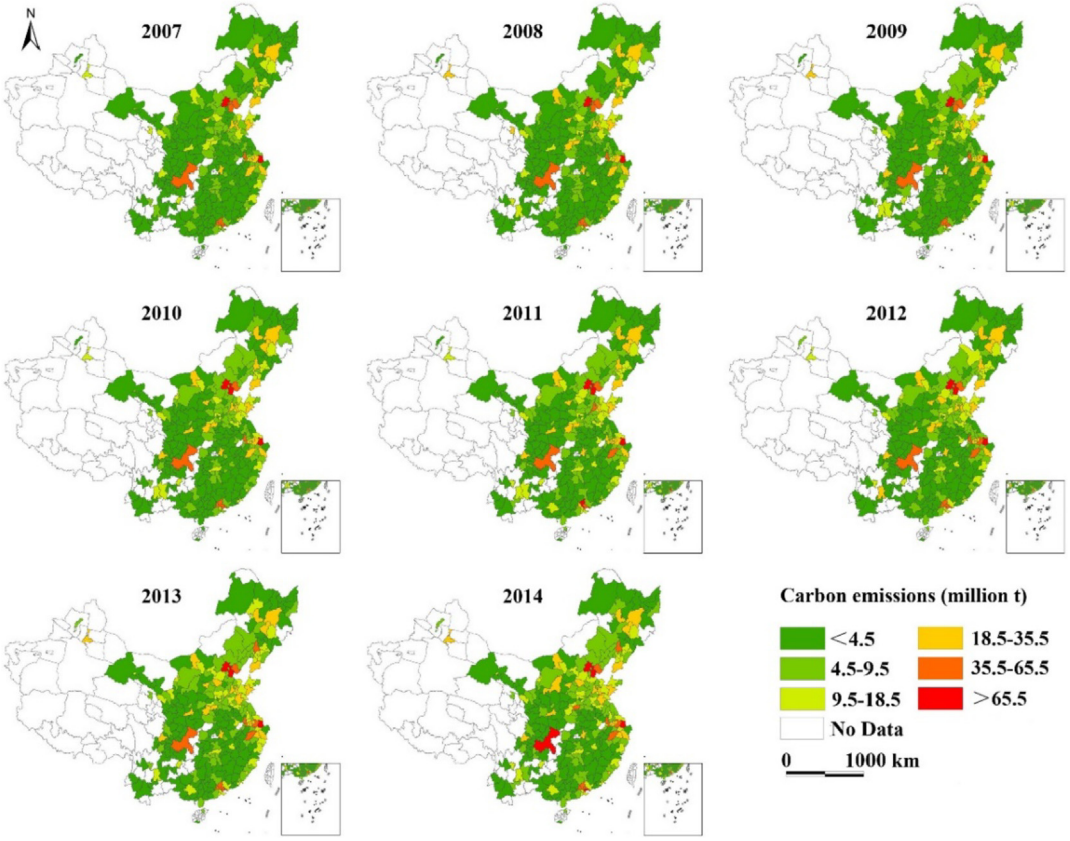

Fig. 2. Spatial patterns of CO_2 emissions from 286 municipal cities in China, 2007–2014.

comparatively fast (e.g., 11.37% more in 2011 compared with that in 2010). After 2012, the CO_2 emission growth gradually slowed. The turning point in CO_2 emission growth in the north was earlier than in the south. The spatial distribution of average CO_2 emissions in municipal cities of China also show highs in the east and lows in the west; the eastern region had the highest emissions followed by the northeast. Cities with the highest CO_2 emissions included Beijing, Shanghai, Guangzhou, and Shenzhen. Chongqing, Wuhan,

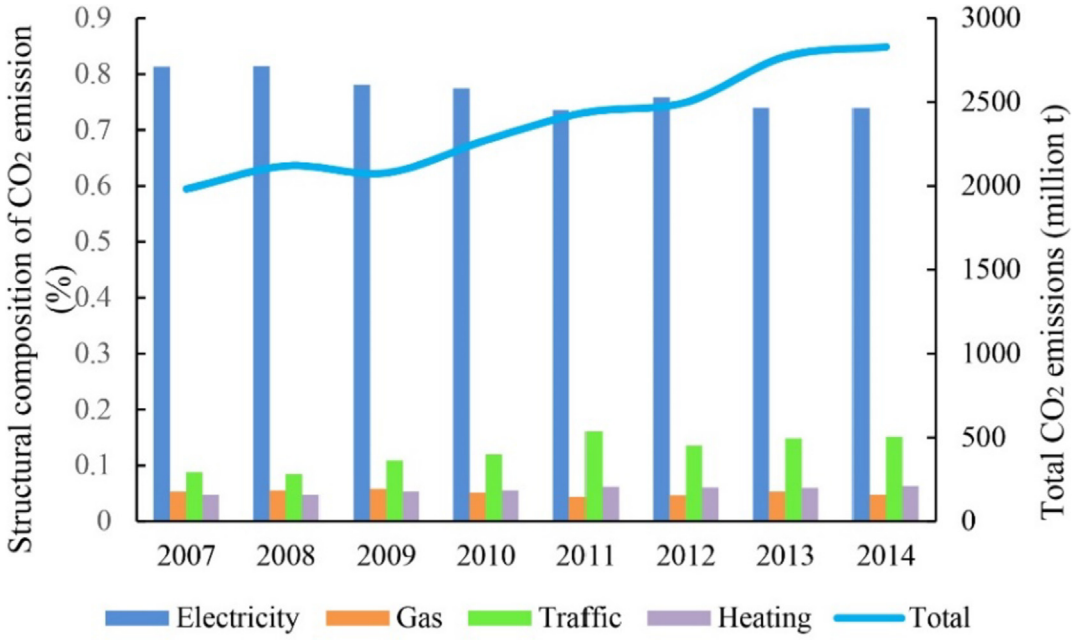

Fig. 3. Structural composition of CO_2 emissions from different energy sectors (left axis) and total CO_2 emissions from 286 municipal cities in China (right axis), 2007–2014.

Table 2
Comprehensive weights for each poverty alleviation index.

Index	Weight	Secondary Index	Weight	Comprehensive weight
Material Poverty Alleviation	0.6	Net income per rural capita	0.225	0.1346
		Disposable income of urban residents	0.251	0.1504
		Per capita GDP	0.1635	0.0981
		Total social retail sales	0.156	0.0933
		Gross investment in fixed assets	0.184	0.1103
Civilization Poverty Alleviation	0.4	Number of enrolled students	0.241	0.0966
		Public library books per 100 people	0.159	0.0639
		Beds in medical and health institutions per capita	0.232	0.0931
		Social security coverage ratio	0.185	0.0743
		Internet penetration	0.213	0.0854

Hangzhou, and coastal cities ranked second. Economically underdeveloped districts generally had lower CO_2 emissions, including three provinces in Xiang-Gan-E region (i.e., Hunan, Jiangxi, and Hubei Provinces), four provinces in Shan-Gan-Ning-Chuan region (i.e., Shaanxi, Gansu, Ningxia, and Sichuan Provinces), and three provinces in Qian-Gui-Dian region (i.e., Guizhou, Guangxi, and Yunnan Provinces), as their production and living fossil energy consumption were lower than that in economically developed districts.

The energy CO_2 emission structure for the 286 municipal cities in China (Fig. 3) shows that the proportion of CO_2 emissions from electricity was the largest, followed by transportation. In comparison, the proportions of CO_2 emissions from gas and heating were relatively low. The structural evolution of CO_2 emissions from 2007 to 2014 showed that the proportion of emissions from electricity declined annually at rate of 9.14%, transportation increased from 8% to 15%, and heating carbon and gas consumption were generally stable. Although electric energy consumption dominated, optimizing the structure of electric energy products in recent years resulted in a decline in the proportion of CO_2 emissions from electricity. As the world's largest consumer of automobiles, China's rapid increase in the number of automobiles led to an increase in CO_2 emissions from transportation.

3.2. Poverty-alleviation index

The weights for each index are obtained based on the analytic hierarchy process and Delphi methods (Table 2). Subsequently, the poverty-alleviation index for each city can be calculated, which is used to generate the spatial pattern of China's municipal city-level poverty index (Fig. 4).

The poverty-alleviation index in China's 286 municipal cities shows clear spatio-temporal evolution (Fig. 4). The average value of the poverty alleviation index increased by 25.19% from 2007 to 2014, with clear periodic and rapid growth, indicating that the extent of poverty in China has been effectively alleviated. In

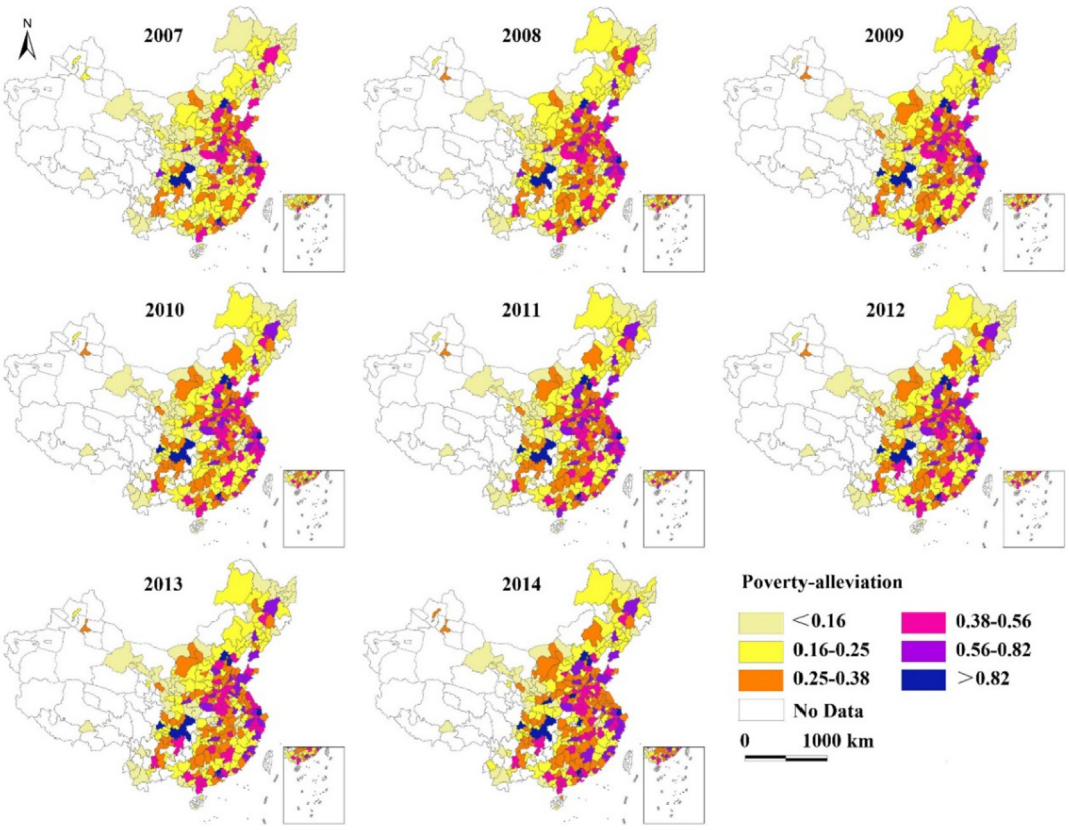

Fig. 4. Poverty-alleviation index spatial distribution for the 286 municipal cities in China, 2007–2014.

Table 3
Analysis of the mechanism influencing CO_2 emissions and social poverty.

Equation 1.pov		Equation 2.em_f		Equation 3.em_st		Equation.co_2	
variable	Coefficient	variable	Coefficient	variable	Coefficient	variable	Coefficient
lnem_f	−0.36*** (-216.55)	$lnco_2$	0.0976 (1.30)	$lnco_2$	0.0895*** (6.25)	lnem_f	0.0502 (1.66)
lnem_st	0.397*** (3.66)	lnpov	−2.783*** (-34.79)	lnpov	0.0167 (1.39)	lnem_st	9.912*** (415.43)
lninc_d	0.000144 (0.01)	lntem	−0.00346 (-0.08)	lngdp_g	0.00115 (0.73)	lnurban	0.0838 (0.77)
lnfor_u	0.00003 (0.01)	lnrain	−0.000237 (-0.01)	lnedu	0.00367 (0.75)	Lnfor_u	−0.00441 (-0.76)
constant	−3.13*** (-5.11)	constant	−6.281*** (-4.09)	constant	2.155*** (9.42)	constant	−19.61*** (-93.02)

*P < 0.1, **P < 0.05, ***P < 0.01.

particular, poverty alleviation increased 14.34% and 5.9% respectively in 2008 and 2014 compared with their respective previous years. These poverty alleviation changes are closely related to China's Three Rural Issues. The Chinese government abrogated agricultural tax in 2006, easing farmer burdens and improving farmer incomes to a certain extent. Accordingly, the rise in the poverty-alleviation index in 2008 was much higher than that in 2007. In 2011, China formally proposed the Targeted Poverty Alleviation Strategy as one of the crucial national development strategies. This strategy considerably increased farmers' income, improved rural development, and facilitated remarkable progress in the countryside, agriculture, and farmer subsistence. From 2012 to 2014, the poverty-alleviation index continuously rose, with the rate of increase significantly higher than that of the previous period. Nevertheless, there remained 181 cities with a lower poverty-alleviation index than the average value by 2014. From this perspective, China still faces enormous pressure and challenges to achieve comprehensive poverty alleviation by 2020. With regard to spatial distribution, the poverty-alleviation index also showed higher values in the east and lower values in the west. The poverty-alleviation index for eastern coastal cities was generally the highest, with the central region ranked second, and the west ranked lowest. Poverty-stricken areas revealed by the poverty-alleviation index are in spatial agreement with China's Rural Poverty Alleviation and Development Program (2011–2020) enacted at the end of 2011 (i.e., the South Foothill of Great Khingan Mountains Zone, Yan-Mountains to Taihang-Mountains Zone, Lvliang Mountains Zone, Liupan Mountains Zone, Dabie Mountains Zone, Qinba Mountains Zone, Wuling Mountains Zone, Luoxiao Mountains Zone, Yunnan-Guangxi-Guizhou Zone, and Mountains Zone of West Yunnan Border). In addition, regions with an increasing poverty-alleviation index (2007–2014) were generally distributed in Guizhou, Jiangxi, and Sichuan, indicating that the targeted strategies were more effective in these poverty-stricken areas.

3.3. Mechanism influencing the relationship between CO_2 emissions and social poverty

The mechanisms influencing the relationship between poverty-alleviation index and employment rate is provided in Table 3. The employment rate in primary industry had a significant negative impact on the poverty-alleviation index ($P < 0.1$). More explicitly, lower employment rates in primary industry resulted in a higher poverty-alleviation index (or lower poverty level). The underlying reason for this relationship is that people who engage in non-agricultural production industries gain more stable and higher income than those in primary industry. Employment rate in non-agricultural industries had a significant positive impact on the poverty-alleviation index ($P < 0.1$). As the national economy has developed, the employment population has gradually transitioned from primary industry to secondary industry, which will transition to tertiary industry as the national income continues to increase. If a country's non-agricultural industry is comparatively developed, national income is higher, which conforms to the Petty-Clark's law. Both the increase in employment rate in non-agricultural industries and decrease in employment rate of the primary industry will contribute to optimizing and upgrading industrial structure, which will stimulate the rapid development of the national economy and accelerate the anti-poverty process. Finally, the net income per rural capita and utilization rate of foreign investment are positively correlated with poverty-alleviation index, but the correlation is non-significant.

The mechanism influencing the relationship between employment rate and CO_2 emissions is also shown in Table 3. The employment rate in the primary industry exerted a positive influence on CO_2 emissions. The sustainable development of agricultural industry increased human activity interference with farmland ecosystems. Labor, chemical fertilizers, pesticides, and mechanical inputs all consume small amounts of fossil fuel energy. However, with regard to the comprehensive employment rate, the impact of employment rate in the primary industry on CO_2 emissions was not the most important. The employment rate in non-agricultural industries had a significantly positive influence on CO_2 emissions ($P < 0.01$). CO_2 emissions increased accordingly when the employment rate in non-agricultural industries increased. This indicates that there were a large number of industries depending on energy input, with high CO_2 emissions, for economic development. Chinese economic development should accelerate the transition to non-agricultural industries and reduce the ratio of high energy consumption industries. Urbanization had a positive effect on CO_2 emissions. This suggests that industrial development, the construction of fundamental urban facilities, and urban resident employment required more fossil fuel energy, which resulted in the continuous growth in CO_2 emissions as rural land, population, capital, and industries transferred to cities.

In summary, a clear indirect mechanism exists between CO_2 emissions and social poverty. They interact through employment rate (i.e., the employment rate in primary industry and non-agricultural industry). There is a positive correlation between CO_2 emissions and employment rate, especially between non-agricultural employment rate and CO_2 emissions. The relationship between employment rate and poverty reduction index is very strong. The employment rate in primary industry and the poverty-alleviation index are negatively correlated, while the non-agricultural employment rate and poverty-alleviation index are positively correlated.

4. Conclusion and discussion

In this study, we measured and calculated CO_2 emissions and the poverty-alleviation index based on socio-economic and energy consumption statistics data from 286 municipal cities in China. We analyzed the relationships between CO_2 emissions, the employment rate, and poverty-alleviation index using a model with simultaneous equations, and interrogated the mechanisms by which CO_2 emissions influence social poverty. The main

conclusions are as follows:

The spatiotemporal changes in the Chinese municipal city-level poverty-alleviation indices and CO_2 emissions from 2007 to 2014 are distinct. Average total CO_2 emissions increased by 32.9%, showing a trend that rapidly increased and transitioned to steady growth. Spatially, CO_2 emissions showed higher values in the east and lower values in the west. The eastern coastal areas had the highest values, while the lowest values were found in the western and southwestern mountainous areas. The average value of the poverty-alleviation index increased by 25.19%, with periodic and rapid growth, indicating that social poverty decreased annually. Spatial disparities in the poverty-alleviation index are clear, decreasing from east to west. The extent of poverty in the eastern coastal cities was lowest, followed by the middle, and was highest in western China.

An indirect feedback mechanism between CO_2 emissions and poverty was identified through the employment rate. A significantly positive correlation was found between CO_2 emissions and non-agricultural employment rate and between CO_2 emissions and employment rate in primary industry. A significant negative correlation was observed between employment rate in primary industry and poverty-alleviation index. In contrast, a significant positive correlation was found between the employment rate in non-agricultural industries and the poverty-alleviation index. The social employment rate improved with increasing CO_2 emissions. The rise in the employment rate strengthens social anti-poverty resilience and reduces the risks of re-poverty. However, to eliminate poverty, it is necessary to develop the industrial economy. This aggregates the impact of CO_2 emissions in intensity and extent. The negative impact brought by CO_2 emissions creates greater socio-economic system losses and objectively reduces the ability of the national population to cope with poverty.

In this study, we examined the multi-directional feedback mechanism between CO_2 emissions, employment rate, and social poverty using econometric methods. We found indirect interactive relationships between CO_2 emissions and social poverty from the chain: energy usage -> emissions intensity -> economic development -> extent of poverty alleviation -> employment and well-being. It is unclear if this chain indicates that the impact of reduced CO_2 emissions on social poverty has gradually decreased to some extent. Based on this assumption, the decoupling of social poverty and CO_2 emissions can be further analyzed through follow-up studies from the perspectives of poverty threshold and poverty gap. Such studies will provide interdisciplinary scientific evidence for implementing CO_2 emissions reduction and anti-poverty strategic projects.

Compared with previous research, the core contributions of this study include the following aspects. Prior work has primarily focused on achieving a single-target, either poverty alleviation or CO_2 reduction, while we unified poverty and CO_2 emissions into one research framework and explored the complex relationship between CO_2 emissions, climate change, employment, and poverty based on the simultaneous equations model. In addition, based on the extent of poverty alleviation, we broke through the limitations of the traditional single (time) node multi-dimensional poverty expression, constructed a quantitative index of poverty alleviation, and intuitively identified the temporal and spatial changes and trends in urban poverty alleviation. Moreover, the validation results in this study will enrich the current literature and provide a reference for future studies.

Despite the breadth of the work, there are some limitations. The data used in this study is consistent with municipal-scale carbon emissions data; however, the poverty alleviation index that we calculated is not accurate to the county scale identified in the "China Rural Poverty Alleviation and Development Program (2011–2020)." In future research, we will further explore county-level CO_2 emissions data. Second, this study links CO_2 emissions and poverty alleviation through employment rates. Although the simultaneous equations model were verified, the mechanism driving their mutual influence is more complex. In follow-up studies, more appropriate instrumental variables should be introduced to improve the analyses to obtain more accurate scientific results.

Conflicts of interest

The authors declare no conflicts of interest.

Acknowledgments

This research was financially supported by the National Program on Key Research Project, China (Grant No. 2016YFA0602500).

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